UNIVERSIDADE CATÓLICA PORTUGUESA

Does bank credit risk impact deposit allocation in commercial banks?

The case of US commercial banks

Master's Final Assignment in the Modality of Dissertation
Presented to the Catholic University of Portugal
To partil fulfilment of the requirements for the degree
of Master of Business Economics

by

Gonçalo Tavares Ferreira Ciravegna da Fonseca

Supervised by
Prof. Ricardo Miguel Ribeiro

Católica Porto Business School
June 2017

Acknowledgements

I would like to express my deepest gratitude and thanks to all that have contributed to this achievement, in particular:

My family, specially my parents and sister, for all the support and motivation during all my academic path, but also during the crucial moments of my life;

My friends, who have been by my side in both good and bad situations;

Prof. Ricardo Ribeiro, for his invaluable orientation, patience and support during the development of this Master thesis. His feedback and opinions were essential to its realization.

Abstract

In the last years, with the occurence of many financial banking crises worldwide, bank credit risk has been a focus of the market. This thesis aims to analyse whether depositants do care about bank credit risk when they allocate their deposits in commercial banks or not. The literature rarely focuses on this crucial relationship between bank credit risk and deposit demand.

In order to further develop this topic, a demand model was defined and estimated applying the characteristic methodology and using multinomial logit and nested multinomial logit specifications. Many bank observed characteristics were included, such as deposit interest rate, service fees, number of branches, number of employees, bank size and bank credit risk.

Using a sample of US commercial banks between 2009 and 2015, findings suggest that depositors react to deposit interest rates and bank size in a positive and statistically significant way when choosing a bank. In addition to that, consumers do care about banks geographic diversification, but they do not consider bank credit risk in a statistically significant way, when deciding their deposits allocation.

Keywords: Credit risk, Depositors, Deposit demand, Demand estimation, Product differentiation.

Resumo

Nos últimos anos, com a ocorrência de várias crises bancárias por todo o mundo, o risco de crédito dos bancos tornou-se um foco para o mercado. Este Trabalho Final de Mestrado tem como objetivo analisar se os depositantes têm em consideração o risco de crédito dos bancos quando decidem alocar os seus depósitos. De facto, este tópico raramente é o foco da análise de pesquisas no setor bancário, que apresentam poucas conclusões neste âmbito.

Com vista ao desenvolvimento deste trabalho, um modelo de procura de depósitos foi definido e estimado, aplicando a metodologia das características e especificações multinomial logit e nested multinomial logit. Várias características observáveis dos bancos foram incluídas na nossa análise, como por exemplo a taxa de juro de depósitos, comissões de serviço, número de balcões, número de empregados, tamanho do banco e risco de crédito.

Tendo por base a análise de bancos comerciais americanos entre os anos 2009 e 2015, as conclusões sugerem que os depositantes reagem à taxa de juro dos depósitos e ao tamanho do banco de uma forma positiva e estatisticamente significativa. Para além disso, os depositantes também têm em consideração a diversificação geográfica dos bancos, mas não reagem ao risco de crédito de uma forma estatisticamente significativa, no momento de alocar os seus depósitos.

Palavras-chave: Risco de crédito, Depositantes, Estimação da procura, Procura por depósitos, Diferenciação dos produtos.

Table of Contents

Index of tables

Index of figures

Chapter 1
Introduction

In the last years, with the occurence of various financial banking crises worldwide, bank credit risk has been a focus of market participants. Between 2009 and 2016, 491 in the US and 4 in Portugal collapsed, resulting in large losses for depositors, investors and shareholders. For example, and only considering 2009 data, 8.14 million dollars were lost by depositors, as a consequence of the failure of Silverton Bank, New Frontier Bank, Community Bank of Nevada and First Bank of Beverly Hills, in the US. In Portugal, and only considering the collapse of Banco Privado Português, depositors lost an estimated value around 700 million euros (Diário de Notícias, 2010). Is, therefore, challenging and crucial to measure credit risk in banking environment.

In this context, this thesis proposes to analyse whether the allocation of deposits by investors and other market participants in commercial banks responds to bank credit risk or not. In other words, it aims to assess if depositors actually consider credit risk in their deposit decision-making process. The literature is very scarce on this topic, with few studies considering the impact of bank credit risk on the demand of deposits as the main focus.

In the US, deposits in insured banks are insured by Federal Deposit Insurance Corporation up to $250,000. As a consequence, it is expected that consumers that allocate their deposits (up to $250,000) in insured banks do not take into consideration bank credit risk. However, the question remains whether the remaining depositors (more than \$250,000 in insured banks and independently of the amount in not insured banks) do respond to credit risk.

To examine this research question, I proposed a quantitative approach through the estimation of a demand model for deposits, applying the characteristic methodology and using multinomial logit and nested multinomial logit specifications. Therefore, banks are considered as a set of observed and unobserved characteristcs. I included deposit interest rates, service fees, the number of branches, the number of employees and bank size as explanatory variables. In addition to that, a variable related with bank credit risk is also used, so that it is possible to capture the impact of bank credit risk on deposit demand.

According to the estimation results of the most flexible and consistent deposit demand specification, depositors respond, in a statistically significant way, to deposit interest rates and bank size. However, they do not react, in a statistically significant way, to bank credit risk when allocating their deposits in commercial banks.

This thesis is organized as follows. Chapter 2, the literature review, has an econometric overview of demand models, presents previous empirical studies on this field and discusses bank credit risk and its measures. Chapter 3 defines the demand model as well as the estimation procedure. In chapter 4, data is described and analysed, while estimation results are presented throughout chapter 5.

Chapter 2
Literature Review

2.1 Demand estimation – econometrics review

Demand estimation is in the basis of several empirical studies that examine a wide range of economic topics, from market power to innovation, mergers and the impact of pricing and non-pricing strategies.

In fact, when choosing a demand model specification, two main concerns must be addressed. First, it must be flexible, in the sense that the selected functional form does not impose restrictions in the data in what concerns substitution patterns. Second, it must be consistent with the economic theory. Early work has been done in this field, for example the linear expenditure model, the Rotterdam model, the translog model and the almost ideal demand system. Even if we define a flexible and consistent demand model, some problems most be solved regarding its estimation: dimensionality problems that are related with large number of parameters to be estimated; empirical problems, specially concerning the use of instrumental variables to face endogenous prices, and unrealistic assumptions, in particular on the distribution of income and types across consumers. Thus, the literature presented demand systems in product space and demand systems in characteristic space as solutions for the mentioned problems.

The multi-stage demand approach in product space assumes that we can divide consumer's decision problem in separate but related stages (top stage, middle stage and lower stage) by splitting products into smaller groups, being products within a group better substitutes to each other than products from different groups. Although this approach allows to solve the dimensionality problem while relying on flexible functional forms, the lower stage can not be estimated for datasets with entry and exit of products, in other words, in this case the procedure is not consistent with economic theory.

Considering products as a set of observed and unobserved characteristics, demand systems in characteristic space solve some of the mentioned problems. Following a discrete choice demand approach, each consumer evaluate whether to buy at most one unit of a product within the inside options or spend the resources in an alternative outside option. The multinomial logit demand model (MNL), although allowing for a large number of dimensions related with consumer heterogeneity and having an analytical demand function, makes assumptions that have strong implications. In particular, it imposes restrictive substitution patterns, as own and cross-price elasticities depend only on the price and market share of the product whose price is being altered and not by how similar the products are. For example, if we introduce an irrelevant alternative, we expect the new product to have little impact but the MNL model does not fit with this intuition. While it maintains an analytical demand function, the nested multinomial logit model (NMNL) reduces some of the previous concerns by integrating a two-stages decision-making process, first choosing which group of products to buy from and, then, deciding between the products of the group. By allowing consumer preferences to be correlated within product groups, the NMNL substitution patterns are more flexible as products that belong to the same group have different substitution patterns from products that belong to different groups. However, cross-price elasticities must take one of two values whether the products belong to the same group or not, being restrictive.

Although there are demand models whose implied substitution patterns are more realistic and flexible, they imply complex estimation procedures.

2.2 Empirical studies on deposits demand models

Applying the refered demand models approaches, several authors conducted empirical researches on pertinent economic topics through the specification of deposit demand models.

Molnar, Violi and Zhou (2013) analyses the competition on the deposit side between italian retail banks, in other words, they examine whether competition is valuable or harmful and risky. For this purpose, the authors applied a structural demand model for deposit services. Considering the retail banking industry as a differentiated product market, banks are differentiated by their observed and unobserved characteristics. Adopting the NMNL model to estimate the demand function, Molnar, Violin and Zhou (2013) used the net deposit interest rate (average deposit interest rate – average service rate), the number of branches in the market, the number of regions where the bank has presence and the age of the bank as observed characteristics. Logarithm of both the number of regions and branches were included in order to capture their declining effect on demand for deposits. Regarding the nested logit models, two different specifications were included: first, classification of banks into one group and, then, into two groups. Banks were classified into two groups following this criterion: national banks – banks that cover at least 16 regions – and local banks – banks that cover less than 16 regions. OLS and IV estimation methods were applied jointly with fixed effects for regions and years across the several model specifications. The instruments included the ratio of total costs to total assets, ratio of liquid assets to total assets, ratio of bad loans to total assets, exogenous bank characteristics, such as the number of regions and the age dummy variable, and BLP instrumental variables, that correspond to the characteristics of other banks in the market (for example, the average age of all other rival banks and the average of the number of regions where all other banks have at least one branch). The sample is from 2003 to 2007, covering 5 years, 20 regions and 105, 104, 103, 103 and 102 banks, respectively. The results indicated that consumers do respond positively and statistically significant to net deposit interest rate and to the number of branches. On the other hand, they do not value the number of regions where the bank is present and the age of the bank when choosing a bank to allocate their deposits. Conclusions also suggest that banks with an extensive multi-market contact tend to be less competitive, paying lower deposit rates.

Dick (2008) proposes a structural deposit demand model for comercial bank with the aim of measuring the effects on consumers of the changes that occured in bank services due to the 90s' US branching deregulation. Following a discrete-choice approach, considering banks as heterogeneous, a set of characteristics were included in the MNL and NMNL models: service charges, rate paid on deposits, number of local branches per square mile, number of employees per branch, bank size, number of states in which the bank has presence and age of the bank. In the particular case of the NMNL model, banks were divided into two groups based on their geographic diversification: multi-state, operating in more than one state and single-state banks, which have presence in a single state. Both OLS and IV estimation methods were used jointly with bank, market and state fixed effects. In what refers to the choice of instruments, the author included market wages, housing price index, city density, expenses on premises and fixed assets, market average price of purchased funds, a measure of credit risk – the average of non-performing loans –, ratio of equity over assets, the proportion of commitment loans and two indicator variables: one for whether the bank operates in at least one rural area and other for whether the bank belongs to a banking holding company. In addition to those, BLP instruments were also included. The sample covers the period between 1993 and 1999 using data on US comercial banks. Consumers seem to react, in a statistically significant way, to deposit interest rates and, in a less extent, to service fees. Other characteristics that affect the allocation of deposits in a statistically significant way include staffing, geographic density of local branches and bank size. Bank geographic diversification and age are not statistically significant to depositors. Findings of this paper suggested that consumers, if anything, increase their welfare as a consequence of the branching deregulation, although it is not possible to establish a concrete casual relationship from deregulation to welfare.

Molnar, Nagy and Horváth (2006) also applied a deposit service demand function in order to analyse the degree of competition of credit loan and household deposit markets in Hungary. In the specific case of deposit services, MNL and NMNL models were used for three sub-markets: demand, short-term and long-term deposits. Interest rates paid by banks on deposits, fees on deposits, the number of branches, average number of employees in a branch, bank age and size were the characteristics considered. In the NMNL model, banks were classified into three different groups based on their total assets: large banks, medium-size banks and small banks. Only an IV estimation method was employed, jointly with time fixed effects. Molnar, Nagy and Horváth (2006) opt to choose as instruments a measure of credit risk – average of non-performing loans –, capital adequacy ratio, ratio of liquid assets to total assets, operational costs per total assets, share of loans per total assets and the average salary per capita of other banks in a period in addition to BLP instruments. The sample covered monthly data for the period between January of 2003 and December of 2005. In what concerns demand for deposits, depositors react in a statistically significant way positively to the interest rate, number of branches and number of employees per branch and in a negatively to service fees. Results of this paper suggest that competition in the Hungarian banking sector is low with high price-cost margins.

2.3 Bank credit risk

Risk measurement is a problematic issue and several methodologies are presented in the literature.

First, bank credit risk can be assessed by rating agencies such as *Standard & Poor's*, *Moody's* and *Fitch/IBCA*. Rating notations normally follow an alphanumeric scale to evaluate credit risk.

In fact, bank ratings are intended to provide investors and other market participants with credit information and analysis by measuring the probability that a bank will default on its debt obligations and the expected monetary loss that if such a default occurs. The bank rating methodology includes several financial, environmental and structural analyses which include ownership and governance, risk profile and management, operating environment and management priorities and strategies.

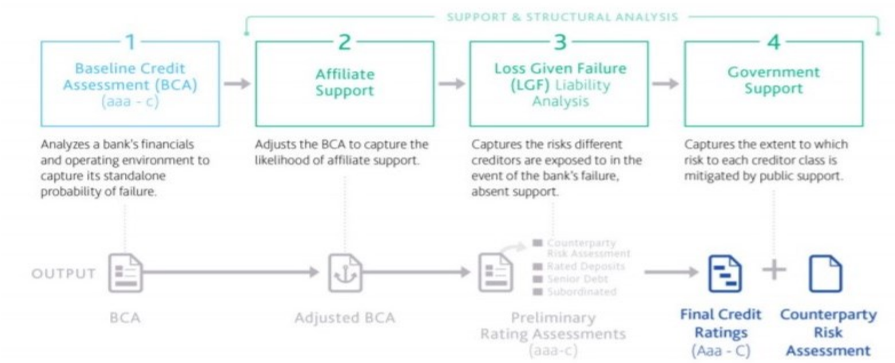

Figure 1: Bank rating methodology. (source: Moody's Investors Services, 1999)

Second, we have the composite measure of asset risk (Dahl and Shrieves, 1992). Following some indexes used in previous researches, this measure is based on accounting data and is a weighted sum of several asset categories divided by total assets. The ratio includes the following components – with the weight of each component being given in parantheses: noninterest-bearing balances and currency and coin (0.00), interest-bearing balances (0.25),short-term US treasury and government agency debt securities (0.10), long-term US government and agency debt securities (0.25), state and local government securities (0.50), bank acceptances (0.25), fed funds sold and securities purchased under agreements to resell (0.25), standby letters of credit and foreign office guarantees (0.75), loan and lease financing commitments (0.25), commercial letters of credit (0.50) and all other assets (1.00). However, using this bank credit risk measure implies having access to restrictive data and information

Furthermore, there are some publicly available measures of loan portfolio quality. As a core credit risk management tool, the portfolio quality analysis focus on past and forecasted portfolio developments. Loan chargeoffs and provisions, loan loss allowances, “past due” and “nonaccrual” loan classifications try to evaluate loan portfolio quality. However, as these measures reflect loan portfolio quality with a lag, they are often biased. In addition to that, having some time discretion over these indicators, there is evidence that banks make accounting decisions regarding these items in order to minimize regulatory costs (Moyer, 1990).

Finally, and although being considered a measure of loan portfolio quality, non-performing loans are less subject to timeliness criticism compared with the previous presented indicators. This loan quality index is the ratio of the sum of one-half of loans classified as past due 90 days or more and loans classified as nonaccrual to total loans. Support for the use of such a measure was developed by Meeker and Gray (1987) and Beaver et al. (1989). In fact, the rationale of non-performing loans is that past due loans have less weight in the predictons of future loan chargeoffs, when compared with nonaccrual loans.

Chapter 3
Empirical framework and model

In this section are presented the definition and estimation procedure of the demand models of deposit services applying two different approaches: the MNL and the NMNL demand models. The choice of these frameworks follows the methodology adopted by previous empiral studies on this field, presented in the literature review chapter, specially Dick (2008), Molnar, Nagy and Horváth (2006) and Molnar, Violi and Zhou (2013). Furthermore, the particularties of our sample justify this approach. First, we have entry and exit of banks across the year, so a model in product space could not be applied. In addition to that, the number of banks is big, resulting in a dimensionality problem that is solved through the use of the charachteristic approach. The choosen models present analytical demand functions that do not imply complex estimation procedures.

These demand models are derived following the discrete choice literature. It is assumed that consumers have already decided the proportion of assets they are going to allocate to deposit services, in other words their savings problems, and they only have to choose a bank. As switching costs and fixed costs are significant, it is a realistic assumption to state that consumers choose a single bank for deposit services.

3.1 Model definition

3.1.1 Multinomial Logit Demand Model

Considering a MNL demand specification for deposit services and assuming that there are $i=1, \ldots, I_t$ consumers interested in purchasing deposit services from a bank, $j=0,1, \ldots, J_t$ banks (j=0 indicates the outside option) and $t=1, \ldots, T$ time periods, the conditional indirect utility of consumer i from choosing bank j's services in year t is:

$$u_{ijt} = \delta_{jt} + \epsilon_{ijt} = \lambda risk_{jt} + \alpha^d p_{jt}^d + \alpha^s p_{jt}^s \alpha^s + x_{jt}'\beta + \xi_{jt} + \epsilon_{ijt},$$

where u_{ijt} is the conditional indirect utility of consumer i from choosing bank j's services in year t, $risk_{jt}$ is a credit risk variable of bank j in year t, p_{jt}^d represents the interest rate paid on deposits of bank j in year t, p_{jt}^s represents the service fees on checking accounts of bank j in year t, x_{jt}' is a K dimensional vector of observed characteristics other than interest rates of bank j in year t, ξ_{jt} represents the unobserved bank characteristics to the econometrician of bank j (included as a mean across consumers) and ϵ_{ijt} is a random disturbance with zero mean, identically and independently distributed (i.i.d) across consumers, banks and time periods. The K+3 dimensional vector $\theta_D = (\lambda, \alpha^d, \alpha^s, \beta)$ denotes the taste parameters to be estimated. $\delta_{jt} = \lambda risk_{jt} + \alpha^d p_{jt}^d + \alpha^s p_{jt}^s \alpha^s + x_{jt}'\beta + \xi_{jt}$ is the mean utility across consumers of bank j in year t. In fact, we can note that the parameters of the utility function do not depend on individual i's characteristics and the variation in consumers' taste enter only through the additive term ϵ_{ijt}. Therefore, consumer i will choose bank j whenever it gives the highest utility, i.e. $U(risk_{jt}, p_{jt}^d, p_{jt}^s, x_{jt}, \xi_{jt}, \epsilon_{ijt}; \theta_D) \geq U(risk_{lt}, p_{lt}^d, p_{lt}^s, x_{lt}, \xi_{lt}, \epsilon_{ilt}; \theta_D)$ for all $l \neq j$, where ϵ_{ijt} and ϵ_{ilt} capture consumer specific terms not observed by the econometrician. By assuming that the consumer heterogeneity term, ϵ_{ijt}, is i.i.d across banks, consumers and time periods and has a standard type I extreme value density function:

$$f(\epsilon_{ijt}) = e^{-\epsilon_{ijt}}\ e^{-e^{-\epsilon_{ijt}}}$$

we can obtain an entirely analytical expression for all the aggregate demand functions:

$$q_{jt}(\delta_t) = S_t \frac{e^{\delta_{jt}}}{\sum_{k=0}^{J_t} e^{\delta_{kt}}}$$

where q_{jt} is the aggregate demand of bank j in year t, in this case the total deposits of bank j in year t, S_t is the market size measure in year t, which, for example, can be defined as the number of consumers or total deposits. $\delta_t = (\delta_{0t}, \delta_{1t}, \dots, \delta_{Jt})$ is a vector of the mean utilities across consumers. Furthermore, this demand model can be established in terms of market shares and, as a consequence, we have:

$$s_{jt}(\delta_t) = \frac{q_{jt}(\delta_t)}{S_t} = \frac{e^{\delta_{jt}}}{\sum_{k=0}^{J_t} e^{\delta_{kt}}}$$

where s_{jt} is the market share of bank j in year t and $\sum_{j=0}^{J_t} s_{jt}\left(\delta_j\right) = 1$.

In what concerns the implied substitution patterns of this model, for example the own- and cross-deposit interest rate elasticities are given by:

$$\eta_{jjt} = \frac{\partial s_{jt}(\delta_t)}{\partial p_{jt}^d} \frac{p_{jt}^d}{s_{jt}(\delta_t)} = -\alpha^d p_{jt}^d [1 - s_{jt}(\delta_t)]$$

$$\eta_{jkt} = \frac{\partial s_{jt}(\delta_t)}{\partial p_{kt}^d} \frac{p_{kt}^d}{s_{jt}(\delta_t)} = \alpha^d p_{kt}^d s_{kt}(\delta_t)\ \ for\ j \neq k$$

where η_{jjt} refers to the own-deposit interest rate elasticity of bank *j* in year *t* and η_{jkt} refers to the cross-deposit interest rate elasticity between bank *j* and *k* in year t. We can note that the MNL model imposes unrealistic substitution patters, specially concerning cross-deposit interest rate elasticities as they are entirely determined by the parameter α^d, the market share and deposit interest rate of the bank whose deposit interest rate is changing, not considering how good substitutes banks are and similar in terms of characteristics.

3.1.2 Nested Multinomial Logit Demand Model

The MNL demand model imposes restrictive substitution patterns, which are not consistent with economic theory. Therefore, the NMNL model reduces this limitation, maintaining a simple and analytical demand function, by requiring an a priori grouping of banks into *G+1* exhaustive and mutually exclusive sets, including the outside good

Following this model, the conditional indirect utility function of consumer i from choosing bank j's deposit services in year t takes the following form:

$$u_{ijt} = \lambda risk_{jt} + \alpha^d p_{jt}^d + \alpha^s p_{jt}^s + x_{jt}'\beta + \xi_{jt} + \{\varsigma_{igt} + (1-\sigma)\epsilon_{ijt}\}$$

where ς_{igt} represents consumer i utility, common to all banks belonging to group g, in year t and σ is an unknown parameter that is restricted to $\sigma \in [0,1[$ in order to be consistent with the economic theory. By including the term ς_{igt}, this model introduces a correlation in the preferences of each consumer across banks within a group. ς_{igt} has a distribution that depends on σ, meaning that if σ converges to one, then increases the relative weight on ς_{igt} and, therefore, the correlation between tastes of banks within a group. On the other hand, if σ converges to zero, the NMNL model approaches the MNL model, previously presented. As proved by Cardell (1997), if ϵ_{ijt} is a type I extreme value random variable, so it is $\{\varsigma_{igt} + (1-\sigma)\epsilon_{ijt}\}$. This assumption produces an analytical expression for the aggregate demand functions of bank $j \in$ group g:

$$q_{jt}(\delta_t) = S_t \frac{e^{\frac{\delta_{jt}}{(1-\sigma)}}}{D_{gt}^{\sigma}\left[\sum_{k=0}^{G} D_{kt}^{(1-\sigma)}\right]}$$

where $D_{gt} = \sum_{k\in g} e^{\frac{\delta_{kt}}{(1-\sigma)}}$ and refers to the inclusive value term of group g in year t. Applying this logic to the market shares:

$$s_{jt}(\delta_t) = \frac{q_{jt}(\delta_t)}{S_t} = \frac{e^{\frac{\delta_{jt}}{(1-\sigma)}}}{D_{gt}^{\sigma}\left[\sum_{k=0}^{G} D_{kt}^{(1-\sigma)}\right]}.$$

For example, the own- and cross-deposit interest rate elasticities implied by the NMNL model are given by the following expressions:

$$\eta_{jjt} = \frac{\partial s_{jt}(\delta_t)}{\partial p_{jt}^d}\frac{p_{jt}^d}{s_{jt}(\delta_t)} = \alpha^d p_{jt}^d[s_{jt}(\delta_t) - \frac{1}{1-\sigma} + \frac{\sigma}{1-\sigma}s_{jt/g}(\delta_t)]$$

$$\eta_{jkt} = \frac{\partial s_{jt}(\delta_t)}{\partial p_{kt}^d}\frac{p_{kt}^d}{s_{jt}(\delta_t)} = \alpha^d p_{kt}^d[s_{kt}(\delta_t) + \frac{\sigma}{1-\sigma}s_{kt/g}(\delta_t)] \ for\, j,k \in g$$

$$\eta_{jkt} = \frac{\partial s_{jt}(\delta_t)}{\partial p_{kt}^d}\frac{p_{kt}^d}{s_{jt}(\delta_t)} = \alpha^d p_{kt}^d s_{kt}(\delta_t) \ for\, j \in g, k \notin g$$

where $s_{jt/g}$ is the within group market share of bank j belonging to group g in year t, in other words, the market share of bank j, which belongs to group g, as a fraction of the total group share s_{gt}.

In fact, the substitution patterns are now much more flexible than the ones proposed by the MNL model due to the fact that now we have different cross-price elasticities depending on whether banks belong to the same group or not. However, the cross-deposit interest rates elasticities still do not depend on bank j, which remain restrictive.

3.2 Model Estimation

3.2.1 Multinomial Logit Demand Model

Following Berry (1994) approach, by matching the predicted market shares to the observed ones and normalizing the mean utility of the outsider option to zero, so that $e^{\delta_{0t}} = 1$, we can derive the equation to estimate the logit model.

First, the MNL predicted market share of bank j in year t should be set exactly to the observed one:

$$s_{jt}(\delta_t) = s_{jt}^*$$

where s_{jt}^* is the observed market share of bank j in year t. Then, dividing the equation by the equality refering to the outside option:

$$\frac{s_{jt}(\delta_t)}{s_{0t}(\delta_t)} = \frac{s_{jt}^*}{s_{0t}^*}$$

and as $e^{\delta_0} = 1$, due to normalization procedures, the market share of the outside good takes the form:

$$s_{0t}(\delta_t) = \frac{1}{\sum_{k=0}^{J_t} e^{\delta_{kt}}}.$$

Substituting in the equation:

$$\frac{s_{jt}(\delta_t)}{s_{0t}(\delta_t)} = \frac{\frac{e^{\delta_{jt}}}{\sum_{k=0}^{J_t} e^{\delta_{kt}}}}{\frac{1}{\sum_{k=0}^{J_t} e^{\delta_{kt}}}} = \frac{s_{jt}^*}{s_{0t}^*}$$

and simplifying the expression we have:

$$e^{\delta_{jt}} = \frac{s_{jt}^*}{s_{0t}^*}.$$

Applying the logarithm of the above equation we get:

$$ln\left(s_{jt}^*\right) - ln(s_{0t}^*) = \delta_{jt} = \lambda risk_{jt} + \alpha^d p_{jt}^d + \alpha^s p_{jt}^s \alpha^s + x_{jt}'\beta + \xi_{jt}$$

which is the MNL model expression – a linear equation that can be estimated by treating the term ξ_{jt} as the error term.

3.1.2 Nested Multinomial Logit Demand Model

Berry (1994) also applied a methodology to estimate the NMNL model. By setting the predicted market shares equal to the observed market shares:

$$s_{jt}(\delta_t) = s_{jt}^*$$

and dividing the equation by an equality referent to the outside option, we get:

$$\frac{s_{jt}(\delta_t)}{s_{0t}(\delta_t)} = \frac{s_{jt}^*}{s_{0t}^*}$$

where $s_{0t}(\delta_t) = \frac{1}{\left[\sum_{k=0}^{G} D_{kt}^{(1-\sigma)}\right]}$. Substituting in the equation, we have:

$$\frac{s_{jt}(\delta_t)}{s_{0t}(\delta_t)} = \frac{\frac{e^{\frac{\delta_{jt}}{(1-\sigma)}}}{D_{gt}^{\sigma}\left[\sum_{k=0}^{G} D_{kt}^{(1-\sigma)}\right]}}{\frac{1}{\left[\sum_{k=0}^{G} D_{kt}^{(1-\sigma)}\right]}} = \frac{s_{jt}^*}{s_{0t}^*}$$

and simplifying this equation:

$$\frac{e^{\frac{\delta_{jt}}{(1-\sigma)}}}{D_{gt}^{\sigma}} = \frac{s_{jt}^{*}}{s_{0t}^{*}}.$$

Applying the logarithm of the above equation, we get:

$$ln(s_{jt}^{*}) - ln(s_{0t}^{*}) = \frac{\delta_{jt}}{(1-\sigma)} - \sigma ln(D_{gt})$$

which is an expression dependent on the inclusive value term D_{gt}. As we set the predicted market shares equal to the observed market shares, the predicted within group market shares will also match the observed ones:

$$s_{jt/g}(\delta_t) = \frac{e^{\frac{\delta_{jt}}{(1-\sigma)}}}{D_{gt}} = s_{jt/g}^{*} \; for \; all \; j \in g.$$

where $s_{jt/g}^{*}$ represents the observed within group market share of bank *j*, that belongs to group *g*, in year t. Applying the logarithm, we get:

$$ln(s_{jt/g}^{*}) = \frac{\delta_{jt}}{(1-\sigma)} - ln(D_{gt})$$

which means that:

$$ln(D_{gt}) = \frac{\delta_{jt}}{(1-\sigma)} - ln(s_{jt/g}^{*}).$$

Substituting this expression, we have:

$$ln(s_{jt}^{*}) - ln(s_{0t}^{*}) = \frac{\delta_{jt}}{(1-\sigma)} - \sigma[\frac{\delta_{jt}}{(1-\sigma)} - ln(s_{jt/g}^{*})]$$

and simplifying, we get:

$$ln(s_{jt}^{*}) - ln(s_{0t}^{*}) = \delta_{jt} + \sigma\, ln(s_{jt/g}^{*}) = \lambda risk_{jt} + \alpha^{d} p_{jt}^{d} + \alpha^{s} p_{jt}^{s} + x_{jt}^{'}\beta + \sigma ln(s_{jt/g}^{*}) + \xi_{jt}$$

which is the NMNL model expression – a linear equation that can be estimated by treating the term ξ_{jt} as the error term. The NMNL is similar to the MNL model, differing by the additional term $\sigma ln(s_{jt/g}^{*})$.

Chapter 4
Data and variables

Balance sheet and income statement data was collected from www.usbanklocations.com. The collected data refers to US commercial banks and covers the period 2009-2015 (7 years) and data is taken from the last quarter of each year. An observation is defined as bank-year combination in the estimation exercise.

4.1 Heterogeneity and product differentiation

In the analysis, we defined deposit services as our product. Thus, it is assumed that depositants consider banks heterogeneous, being the differentiating factors the characteristics of banks.

In fact, two different prices are considered: the interest rate paid on deposits and service fees and comissions. The deposit interest rate is calculated by the ratio of deposit expenses, both domestic and foreign, to the stock of deposits, while deposit service charges are calculated by the ratio of deposit revenues from fees and commissions to the stock of deposits. Related with service fees, we also included a dummy variable that should capture the impact of banks charging deposit service fees because, in our sample, some banks do not do that. This dichotomous variable whether assumes the value 1 if the bank actually charges deposit servisse fees or 0 otherwise.

Being sources of heterogeneity, some observed bank characteristics are included in our model, starting with the number of branches that should be related with banks' spatial and geographical differentiation. We also used the number of employees in order to capture its correlation with waiting time and the value of human interaction to depositants. Bank size is another characteristic that is controled in our model. Dick (2008) applied three size categories based on total assets: small, medium and large.[1] However, we found out that, following this criterion, all banks in our sample are considered large. Thus, taking into consideration total assets, we defined two groups in order to analyse the impact of bank size on the demand of deposits: large banks and too big to fail banks. According to Labonte (2017), banks with more than 300 billion assets are declared too big to fail. This variable *toobigtofail* is included with the objective of capturing features related with larger banks, for exemple bundle of products and services, infrastructures and know.

Bank age was also a characteristic we use through a dummy variable intended to measure the impact of reputation, branding, reliability and expertise, by dividing banks into two categories: experienced banks, which have activities for 15 or more years and recent banks, which are established for less than 15 years - following Molnar (2013). We also introduced the number of states in which the bank has presence, intended to capture the value of network size and geographic diversification. However, we have to drop these two characteristics due to collinearity problems, as we used bank and year fixed effects in our specifications.

In addition to that, and being the focus of this master thesis, a bank credit risk measure is included in our data in order to assess the impact of credit risk on the allocation of deposits. Deciding the right measure for bank credit risk was a

[1] Banks with total assets between 100 and 300 million are considered medium-sized, while banks with total assets above 300 million are considered large. This criterion is defined according to the FFIEC form that banks report to the regulatory authority.

challenging task. In fact, based on previous empirical analysis, we decide to use the ratio of non-performing loans for measuring bank credit risk. This variable is calculated by the ratio of non-performing loans, which are calculated by the sum of one-half of loans classified as past due 90 days or more and loans classified as nonaccrual, to total loans:

$$riskv_{jt} = \frac{\frac{1}{2} \times lpd_{jt} + nal_{jt}}{loans_{jt}} \times 100$$

where $riskv_{jt}$ is the ratio, in percentage, of non-performing loans of bank j in year t, lpd_{jt} is a variable that measures loans past due 90 days or more of bank j in year t, nal_{jt} corresponds to nonaccrual loans of bank j in year t and $loans_{jt}$ represents total loans of bank j in year t.

The risk measure I am using, $risk_{jt}$, will be defined as a dummy variable that have the value 1 if the ratio of non-performing loans of the bank in that year is above the median and the value 0 if that ratio is equal to or under the median.

4.2 Market and outside option definition

Defining the relevant market measure is an essential step in our analysis. In fact, as we have explained in the previous section, market shares depend on how we specify market size. Considering the deposit banking market of the US as a whole, the market share of a bank in a year is calculated by the ratio of the bank stock of deposits that amounts at the end of the year to the whole market size. S_t, the market size in year t, is defined as the sum of the stock of deposits at the end of year t of all US commercial banks.

In what regards the definition of the outside option, Molnar (2006) and Dick (2008) considered thrifts and credit unions arguing that these depository institutions are likely bank competitors. Although that might be a possible definition to the outside option, due to data limitation on these fields, other approach was followed. Therefore, our outside option in year t is defined as the sum of the stock of deposits at the end of the year from banks that do not have a market share above 0.5% in any of the 7 years of the data sample – this approach is also used in Pinkse (2004).

So, the market share of bank j in year t is calculated by the ratio of the stock of deposits, at the end of the year t, of bank j to the stock of deposits of all banks in year t.

Therefore, we have 48 commercial banks in 2009, 49 in 2010 and 2011, 47 in 2012, 48 in 2013 and 2014 and 49 in 2015.

4.3 Groups

To carry the estimation of the nested logit demand model, an a priori grouping of banks into groups is required. Following previous empirical studies on this field, we used two different criteria.

On one hand, we divide banks into two groups based on their total assets. The first group includes 252 banks with total assets above 300 billion – banks too big to fail. In the second group, 86 banks – large banks.

One the other hand, banks were grouped based on their geographic diversification: multi-states banks, operating in more than one state, and single state banks, which have presence in a single state. Considering the sample, the first group – multi-state banks – has 244 banks and the second group – single state banks – has 94 banks. This grouping criterion should insure that differences in terms of banks' geographic presence are included in the model. Therefore, single state banks, which do not operate in more than one state, tend to be present in a single local market within the state, being considered local banks. Otherwise, multi-state banks, which have presence in more than one state, tend to have the caractheristic of establishing operations in more than one local market within the states.

4.4 Endogeneity and instrumental variables

As discussed before, the term ξ_{jt} is the error term of both the MNL and NMNL demand models. In fact, this term has a significant meaning: the unobserved characteristics of bank j in year t, including variables such as reputation, credit conditions that are not interest rates, advertising and promotions, financial soundness and experience. Although they are not observed by the econometrician, banks and consumers do observe and react to them. These characteristics may also be correlated with prices, which make them endogenous. Therefore, the simple OLS estimates can be biased and we should use the instrumental variables (IV) estimation method in order to control the endogeneity issue. Besides deposit interest rate and service fees, in the NMNL, the term $ln(s_{jt/g})$ is clearly endogenous and also needs to be instrumented. This happens because the within group share is correlated with the prices and, as a consequence, with the unobserved characteristics, in other words, the error term. With the inclusion of bank fixed effects, which capture the mean valuation of banks' unobserved characteristics across years, and year fixed effects, that capture the mean valuation of unobserved characteristics of a given year, the error term is now defined as deviations from the mean the mean valuation, which includes demand shocks.

The selected instrumental variables must satisfy two conditions: they need to be correlated with the endonegous variables and not correlated with the error term.

Following Dick (2008), the set of instrumental variables includes two parts: cost shifters and markup shifters. On one hand, we have the cost shifters, which are, by definition, not correlated with demand shocks included in the error term, but are correlated with pricing decisions and, therefore, with the endogenous variables. The cost shifthers include the degree of a bank capitalization, measured by the ratio of equity over assets, the capital adequacy ratio, the ratio of liquid assets to total assets and the share of loans per total asset. In addition to that, we use the labour cost per total asset to measure labour costs and, to control operating costs, the ratio of expenses on premises and fixed assets to total deposits. For the within group market share of a given bank, we use the mean of the cost shifters instruments across groups.

On the other hand, BLP variables were included. These standard variables of the discrete choice literature refer to the characteristics of other banks in the same year as instruments for prices. The underlying rational of this approach is that characteristics other than prices are exogenous and not correlated with the error term but correlated with the price of other banks. This happens because banks that have close substitutes will have lower markups while other banks will have higher prices compared with costs. In the NMNL model specification, characteristics of other banks in the group were used as instruments for the within market share of a given bank.

4.5 Summary statistics

In this section, Table 1 is presented, which provide the summary statistics of our variables.

Variable	Mean	Median	Min	Max	St. dev.
Number of branches	884.763	360.000	1.000	6393.000	1470.542
Number of employees	26752.970	9946.000	6.000	231333.000	50753.400
Non-performing loans (%)	1.845	1.309	0.000	8.469	1.621
Bank credit risk (Y/N)	0.500	0.500	0.000	1.000	0.501
Too big to fail (Y/N)	0.746	1.000	0.000	1.000	0.436
Market share (%)	1.447	0.533	0.044	12.171	2.596
Deposit interest rate (%)	0.514	0.307	0.011	3.629	0.562
Service fees (Y/N)	0.811	1.000	0.000	1.000	0.392
Service fees (%)	0.257	0.261	0.000	0.845	0.236
Equity/Assets (%)	12.274	11.888	5.894	34.495	3.795
Capital adequacy ratio (%)	16.219	14.665	10.665	70.284	5.902
Liquid assets/Assets (%)	73.878	76.308	30.932	93.165	12.084
Loans/Assets (%)	57.004	63.674	0.296	97.184	21.101
Labour costs/Assets (%)	1.004	1.190	0.008	2.210	0.543
Operating costs/Deposits (%)	0.339	0.364	0.001	1.074	0.215

Table 1: Summary statistics.
Note: The statistics were computed across 338 observations

From Table 1, we can state that the median bank in the median year has 360 branches, 9946 employees, has a ratio of non-performing loans of 1.309% and is classified as a too big to fail bank. This median bank has a market share of 0.533%, offers a deposit interest rate of 0.307% and charges service commissions with a value of 0.261%.

Table 1 is also presentes the summary statistics refered to the cost shifters instruments. The mean bank in the median year has a ratio of equity over assets of 11.888%, a capital adequacy ratio of 14.665%, a ratio of liquid assets to total assets of 73.308%, a ratio of loans to total assets of 63.674%, a ratio of labour costs, which include wages, to total assets of 1.19% and a ratio of operating costs to total deposits of 0.364%.

4.6 Preliminary analysis of the impact of bank credit risk

Analysing the average market share depending on the value of the dummy of credit risk, in other words, depending on whether the bank has a credit risk measure above the median or not, we have:

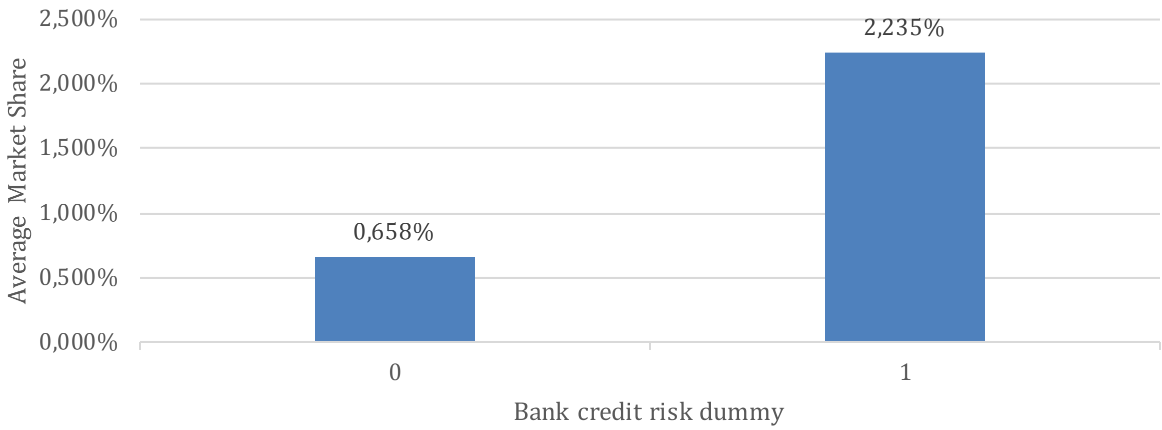

Figure 2: Average market share depending on the value of the bank credit risk dummy.

From the figure, it is concluded that banks that have a ratio of non-performing loans above the median have higher market shares when compared with banks with a measure of credit risk below the median. In fact, at a first approach, it was expected that high credit risk was not desirable by depositants. However, this can be explained by an indirect effect of the deposit interest rate. Thus, higher credit risk can imply higher deposit interest rates, which attract more depositants, increasing market share.

Chapter 5
Estimation results

As previously explained, and following Berry (1994) approach, the MNL model and the NMNL demand model can be estimated by regressing the logarithm of observed market shares $ln(s_{jt}^{*}) - ln(s_{0t}^{*})$ on prices, which include deposit interest rate and service fees, observed market characteristics, such as number of branches, number of employees and total assets, measure of bank credit risk and, in the NMNL case, the logarithm of the within group observed market share $ln(s_{jt/g}^{*})$.

Table 2 presents the estimation results. Specifications *(i)*, *(ii)* and *(iii)* follow the MNL demand model and are estimated using OLS, while specifications *(iv)*, *(v)* and *(vi)* are estimating using IV, specifically cost shifthers instruments. In addition to that, specifications *(v)* and *(vi)* correspond to the NMNL demand model. Standard errors are adjusted for heteroskedasticy and for correlation of errors within the same year. Throughout the various columns, different fixed effects were included, as refered at the bottom of each column.

In all specifications, we considered the logarithm both of the deposit interest rate and service fees. This happened due to the fact that we found what that there was a non-linear relationship between these two price variables and the market share. In the following sections, we investigate the estimation results in detailed.

Explanatory variable	Specifications OLS (i)	(ii)	(iii)	IV (iv)	(v)	(vi)
ln(Deposit interest rate)	-0.119	-0.089	0.114	0.624	0.250	0.095
	(0.027) ***	(0.022) ***	(0.057) *	(0.108) ***	(0.150) *	(0.046) ***
ln(Service fees)	0.004	0.006	-0.020	-0.074	-0.158	-0.014
	(0.007)	(0.008)	(0.008) **	(0.076)	(0.049) ***	(0.024)
Service fees (Y/N)	0.081	0.065	-0.223	-1.295	-1.262	-0.183
	(0.081)	(0.085)	(0.102) *	(0.661) **	(0.566) **	(0.243)
Bank credit risk (Y/N)	0.025	0.081	0.084	0.185	0.130	0.027
	(0.051)	(0.047)	(0.046)	(0.077) ***	(0.063) **	(0.026)
Number of branches	0.000	0.000	0.000	0.001	0.000	0.000
	(0.000) ***	(0.000) **	(0.000) ***	(0.000) ***	(0.000) ***	(0.000) *
Number of employees	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000) ***	(0.000) ***	(0.000) ***	(0.000)	(0.000) ***	(0.000)
Too big to fail (Y/N)	1.035	1.027	0.257	0.349		0.056
	(0.023) ***	(0.017) ***	(0.033) ***	(0.045) ***		(0.029) ***
ln(sj/g)					-0.002	0.813
					(0.039)	(0.081) ***
R-squared	0.866	0.870	0.981	0.957	0.966	0.999
Fixed effects		Year	Bank Year	Bank Year	Bank Year	Bank Year

Table 2: Estimation results. Note: The results were estimated using 338 observations. Clustered (by year) standard errors are in parenthesis. * denotes significant at 10%, ** denotes significant at 5% and *** denotes significant at 1%.

5.1 OLS regressions

The estimation results of the specification *(i)* indicate that depositants respond significantly to deposit interest rates, number of employees, number of branches and bank size when choosing a bank to allocate their deposits. Deposit interest rates have a negative impact on deposit demand, meaning that high interest rate will not attract depositants. Further, consumers value the number of employees, number of branches and bank size in a positive statistically significant way. Furthermore, depositants seem to do not consider whether the bank charge servicee fees or not in addition to their value. Bank credit risk is also not significantly taken into account in the decision-making process. In fact, the sign of the deposit interest rate coefficient is not consistent with what was expected because this interest rate should affect deposit demand in a positive way. This inconsistency may be caused by endogeneity problems. As explained before, price variables are correlated with the error term and, therefore, estimation parameters are biased.

In specification *(ii)* year fixed effects are included. Estimation results indicate the same conclusions as the ones from specification *(i)*. With the introduction of year fixed effects, the mean valuation of bank unobserved characteristics for a given year are captured, reducing the endogeneity problems. This is evident by the reduction suffered by the value of the coefficient of deposit interest rate, which became less negative.

By adding bank fixed effects in specification *(iii)* the unobserved bank component is also controled. With this feature, some changes in the estimation results occur. First, depositants do not respond to deposit interest rates anymore. Although this happens, consumers now value service fees when choosing a bank to allocate their deposits. They actually react in a negative way if banks charge service fees and respond negatively to high values of service commissions. These changes may be caused by the reduction of the correlation between prices and the error term, through the introduction of fixed effects.

5.2 IV regressions

Estimation results of specifications *(iv)*, *(v)* and *(vi)* are of most interest to us as we use the IV method to fully solve the endogeneity problem.

Instrumental variables are used in specification *(iv)* in order to face endogenous variables and its estimation results are quite interesting. In fact, depositants do respond to deposit interest rate in a positive way, as expected. In addition to that, they also value if banks charge or not service fees, but they do not react to their value. Thus, they prefer to allocate their deposits in banks that do not charge service commissions related with deposits. Besides that, bank credit risk is now taken in consideration. Consumers react to values above the median in a positive way, which does not match previous expectations. The number of employees is not an important factor according to these results.

Specifications *(v)* and *(vi)* apply the NMNL demand model using different group criteria. The first one, assume that banks are grouped according to their total assets into banks too big to fail and large banks. In this specification, the dummy that controls bank size is dropped in order to avoid collinearity issues. According to the results, depositants react to whether a bank charge service fees or not and to these commissions value in a negative way. While they continue to value bank credit risk above the median and the number of branches, they also respond positively to the number of employees. The estimation coefficient for the group segmentation parameter has a negative and insignificant value, meaning that the group variable does not fit well and, therefore, this segmentation criterion is not realistic.

Specification (vi) divide the deposit decision-making process into single state and multi-state banks. In fact, this criterion seems to be realistic according to the results, as σ, which is the coefficient of the logarithm of the within group market share, is significant and has a value between 0 and 1. This estimate is closer to 1, giving support that the correlation between the preferences of banks that belong to the same group is high. According to the estimation results, depositants react to deposit interest rate in a positive way as well as to the bank size. Number of branches are only significant at 10%. Following this specification, consumers do not value bank risk in a significant way, as expected. This specification is the most flexible because it follows the NMNL demand model, imposing less restrictive substitution patterns and is estimated using IV.

Conclusion

The purpose of this paper has been to analyse whether depositors respond to bank credit risk when they allocate their deposits in commercial banks through the estimation of a demand model for deposit services. The model is designed to reflect depositors decision-making process and includes a set of observed characteristics, such as deposit interest rate, service fees, number of branches, number of employees, bank size and bank credit risk.

The results indicated that consumers do respond in a positive and statistically significant way to deposit interest rate and number of branches when concerns demand for deposits. In what regards bank credit risk, a statistically significant relationship between this varible and demand for deposits could not be taken.

The results are limited to sample and data limitation. First, the characteristics of the sample can hinder the analysis. The defined relevant market includes approximately 50 banks per year, which is not representative. Furthermore, and from the summary statistics, the maximum ratio of non-performing loans is 8.469% and the standard deviation 1.621%, revealing that observations are not very dispersed in what concerns this variable. This fact turns hard to find out realistic and consistent relationships on this variable. In addition to that, obtaining reliable data on US commercial banks variables was a difficult task. Besides that, data treatment was a very complex task in this thesis. On the other hand, due to some data limitation, several restrictive assumptions on economic definitions were made.

For further research is highly reccommended to conciliate the economic definitions presented here, in what is related to the outside option and bank credit risk measures, with alternative approaches, so that new results can be obtained. It would be interesting to analyse the relationship between bank credit risk and demand for deposits in not insured commercial banks and other countries.

Bibliography

Ahmed, A., Takeda, C., & Shawn, T. (1998). Bank loan loss provision: A re-examination of capital management and signaling effects. Working paper, Department of Accounting, Syracuse University.

Beaver, W., Eger, C., Ryan, S., & Wolfson, M. (1989). Financial reporting, supplemental disclosures, and bank share prices. *Journal of Accounting Research,* 27, 157-178.

Berry, S. (1994). Estimating discrete-choice models of produc differentiation. *The RAND Journal of Economics*, 25, 242-262.

Berry, S., Levinsohn, J., & Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica,* 63, 841-890.

Cardell, N. (1997). Variance componentes structures for the extreme-value and logistic distributions with application to models of heterogeneity. *Econometric Theory*, 13(02), 185-213.

Dick, A. (2008). Demand estimation and consumer welfare in the banking industry. *Journal of Banking and Finance,* 32(8), 1661-1676.

K. Tumin. (2010, January 3). Reviews on the 2009 bank failures and what depositors experienced. Retrieved from: https://www.depositaccounts.com/blog/review-of-2009-bank-failures-and-what.html

Kargi, H. (2011). Credit risk and the performance of nigerian banks. Working paper, Ahmadu Bello University, Zaria.

Meeker, L., & Gray, L. (1987). A note on non-performing loans as an indicator of asset quality. *Journal of Banking and Finance*, 11, 161-168.

Molnar, J., Nagy, M., & Horváth, C. (2006). A structural empirical analysis of retail banking competition: the case of Hungary. Retrieved from SSRN: www.ssrn.com/abstract=961776

Molnar, J., Violi, R., & Zhou, X. (2013). Multimarket contact in italian retail banking: competition and welfare. *International Journal of Industrial Organization*, 31, 368-381.

Moyer, S. (1990). Capital adequacy ratio regulations and accounting choices in commercial banks. *Journal of Accounting and Economics*, 13, 123-154.

Nevo, A. (2000). A practicioner's guide to estimation of random-coefficients logit models of demand. *Journal of Economics & Management Strategy*, 4, 513-548.

Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica*, 69, 307-342.

Pinkse, J., & Slade, M. (2004). Mergers, brand competition, and the price of a pint. *European Economic Review*, 48, 617-643.

Rebelo, R. (2010, April 17). Milhões de perdas com o BPP. Diário de Notícias. Retrieved from: http://www.dn.pt/bolsa/interior/mil-milhoes-de-perdas-com-o-bpp-1546250.html

Shrieves, R., & Dahl, D. (1992). The relationship between risk and capital in commercial banks. *Journal of Banking and Finance*, 16, 439-457.

Theodore, S. (1999). Bank credit risk rating methodology: an analytical framework for banks in developed markets. Moody's Investors Services Global Credit Research.